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ML-BASED PREDICTION OF MECHANICAL PROPERTIES OF ShKh15 BEARING STEEL OBTAINED FROM SECONDARY MATERIALS

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Abstract

This study presents a machine learning-based approach for predicting the mechanical properties of ShKh15 (AISI 52100) bearing steel produced from secondary raw materials. A dataset comprising 180 experimental samples with varying chemical compositions, heat treatment parameters (austenitizing temperature 820–880°C, tempering temperature 150–250°C), and recycled material ratios (20–80%) was compiled from laboratory testing. Three *ML* models — Random Forest (*RF*), Artificial Neural Network (*ANN*), and Gradient Boosting Regression (*GBR*) — were trained and evaluated for predicting Rockwell hardness (*HRC*), tensile strength (σb), and impact toughness (*KCU*). The *ANN* model with architecture 9-64-32-3 achieved the best performance with $R^2 = 0.9724$ for hardness and *RMSE* = 0.87 HRC. Feature importance analysis identified recycled material ratio (31.4%), austenitizing temperature (22.8%), and carbon content deviation (18.6%) as the most influential parameters. The developed models enable rapid property estimation during bearing steel production from secondary materials, potentially reducing quality control testing by 45–55%.

Keywords

bearing steel, ShKh15, machine learning, mechanical properties prediction, secondary materials, artificial neural network, heat treatment optimization

INTRODUCTION

Bearing steel is one of the most critical structural materials in modern mechanical engineering, directly influencing the reliability and service life of rotating machinery across diverse industrial sectors including automotive, aerospace, energy, and manufacturing [1]. ShKh15 (equivalent to AISI 52100 / 100Cr6) is the most widely used high-carbon chromium bearing steel, characterized by high hardness (60–65 HRC after quenching and tempering), excellent wear resistance, and adequate fatigue life under rolling contact conditions [2]. In Uzbekistan, the demand for bearing components continues to grow with industrial modernization, yet domestic production relies heavily on imported raw materials, creating supply chain vulnerabilities and elevated costs [3].

The utilization of secondary metallic materials — scrap steel, worn-out bearing components, and industrial metal waste — represents a promising approach for sustainable bearing steel production. Previous research has demonstrated the feasibility of producing ShKh15-grade steel from recycled feedstock through electric arc furnace (*EAF*) melting and vacuum degassing [4,5]. However, the inherent variability in scrap composition introduces uncertainty in final product properties, necessitating extensive quality control testing that increases production costs and cycle time [6].

Machine learning (*ML*) methods have emerged as powerful tools for establishing complex structure–process–property relationships in materials science [7]. Unlike traditional empirical models, *ML* algorithms can capture non-linear interactions among multiple input variables without explicit physical modeling. Recent applications include prediction of steel mechanical properties based on composition and processing parameters [8], optimization of heat treatment schedules [9], and quality classification of metallurgical products [10]. Nevertheless, the application of *ML* specifically to bearing steel produced from secondary materials remains largely unexplored.

The present study aims to: (1) compile an experimental dataset of ShKh15 bearing steel properties as a function of recycled material ratio, chemical composition deviations, and heat treatment parameters; (2) train and compare three representative *ML* algorithms (*RF*, *ANN*, *GBR*) for multi-target property prediction; and (3) identify the most influential factors governing the mechanical performance of recycled bearing steel through feature importance analysis.

LITERATURE REVIEW AND METHODOLOGY

The application of machine learning in steel metallurgy has gained significant momentum in recent years. Agrawal and Choudhary [8] demonstrated that deep neural networks can predict ultimate tensile strength of alloy steels with $R^2 > 0.95$ using composition and processing features. Shen et al. [11] applied gradient boosting to predict Charpy impact energy of low-alloy steels, achieving prediction errors within 10% of experimental values. In the specific context of bearing steels, Wang et al. [12] used support vector regression to model the relationship between austenitizing conditions and retained austenite content in 100Cr6 steel.

Baymirzaev et al. [4] reviewed advanced technologies for developing bearing materials, establishing a comprehensive overview of manufacturing routes including casting from secondary feedstock. In a subsequent study, Baymirzaev and Kamoldinova [13] explored the preliminary application of artificial intelligence for predicting properties of novel metal-composite materials intended for bearing applications. Baymirzaev [5] also investigated new methods of obtaining bearing material from steel under local conditions, providing baseline data on achievable property ranges.

Despite these advances, a systematic study combining experimental data from secondary-material ShKh15 production with rigorous *ML* model comparison and feature importance analysis has not been reported. The present work addresses this gap.

Bearing steel specimens were produced by melting secondary metallic feedstock (worn ShKh15 bearing rings, high-carbon steel scrap) in a 50 kg capacity induction furnace at the Andijan State Technical Institute laboratory. The recycled material ratio was systematically varied at 20%, 40%, 60%, and 80% (balance: virgin low-carbon steel and ferrochrome). After melting and refining, specimens were cast into cylindrical ingots (Ø30 × 200 mm) and subjected to homogenization annealing at 800°C for 4 hours. Heat treatment comprised oil quenching from austenitizing temperatures of 820°C, 840°C, 860°C, and 880°C (holding time 30 min), followed by tempering at 150°C, 180°C, 200°C, 220°C, and 250°C for 2 hours. Chemical composition was determined by optical emission spectrometry (*OES*, Spectrolab M12). Mechanical testing included Rockwell C hardness (5 indentations per specimen), tensile testing per GOST 1497 on proportional specimens (gauge length 50 mm, Ø5 mm), and Charpy U-notch impact testing per GOST 9454 at room temperature. A total of 180 unique condition combinations were tested with 3 replicates each.

The *ML* input feature vector comprised 9 variables: C content (wt.%), Cr content (wt.%), Mn content (wt.%), Si content (wt.%), S content (wt.%), P content (wt.%), recycled material ratio (%), austenitizing temperature (°C), and tempering temperature (°C). Three target variables were predicted simultaneously: Rockwell hardness *HRC*, ultimate tensile strength σb (MPa), and impact toughness *KCU* (J/cm²). The dataset was split 80:20 for training and testing with 5-fold cross-validation. *RF* (500 trees, max depth 12), *ANN* (9-64-32-3 architecture, ReLU activation, Adam optimizer, 500 epochs), and *GBR* (300 estimators, learning rate 0.05, max depth 5) were implemented using *scikit-learn* 1.3 and *TensorFlow/Keras* 2.14 in Python 3.11.

RESULTS AND DISCUSSION

Table 1 presents the chemical composition ranges of ShKh15 bearing steel obtained from secondary materials at different recycled ratios, compared with the GOST 801-78 standard specification. As the recycled material ratio increases from 20% to 80%, the scatter in carbon and chromium content widens, reflecting the compositional heterogeneity of scrap feedstock.

Table 1. ***Chemical Composition of ShKh15 Steel at Different Recycled Material Ratios (wt.%)***

Recycled ratio	**C**	**Cr**	**Mn**	**Si**	**S**	**P**
GOST standard	0.95–1.05	1.30–1.65	0.20–0.40	0.17–0.37	≤0.020	≤0.027
20%	0.97–1.02	1.38–1.58	0.22–0.35	0.19–0.33	0.008–0.014	0.010–0.019
40%	0.94–1.04	1.32–1.61	0.21–0.38	0.18–0.36	0.010–0.018	0.012–0.023
60%	0.92–1.07	1.28–1.64	0.19–0.41	0.16–0.38	0.012–0.022	0.015–0.026
80%	0.89–1.09	1.24–1.68	0.18–0.43	0.15–0.40	0.014–0.025	0.018–0.030

At 20–40% recycled content, all compositions remained within GOST specifications. At 60% recycled content, sulfur and phosphorus levels approached specification limits in some heats, while at 80%, occasional exceedances were observed (S up to 0.025%, P up to 0.030%), indicating the need for enhanced refining or stricter scrap selection at high recycling ratios.

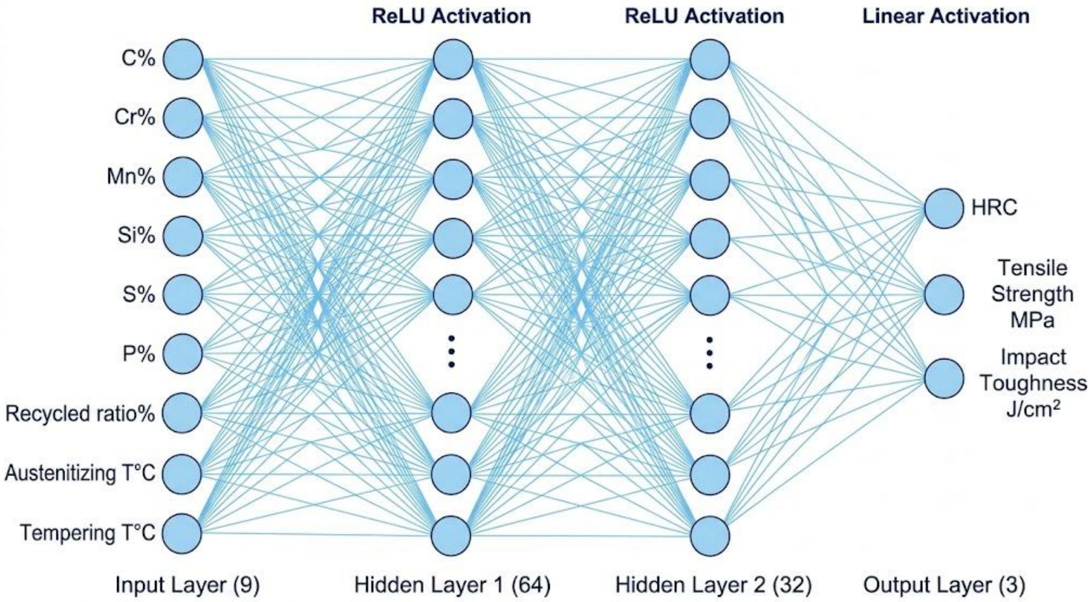

Figure 1. Architecture of the ANN model (9-64-32-3) for multi-target mechanical property prediction of ShKh15 bearing steel

The prediction performance of the three *ML* models is summarized in Table 2. The *ANN* model demonstrated superior performance across all three target properties, with R² values ranging from 0.9412 to 0.9724. *GBR* achieved comparable accuracy for hardness prediction (R² = 0.9618) but showed larger errors for impact toughness. *RF* exhibited the lowest predictive capability overall, particularly for impact toughness (R² = 0.8843), which is known to be sensitive to microstructural features not directly captured by bulk composition parameters.

Table 2. ***Prediction Performance Comparison of ML Models***

Model	**Property**	**R²**	**RMSE**	**MAE**
ANN	Hardness (HRC)	0.9724	0.87	0.64
ANN	Tensile Strength (MPa)	0.9651	18.3	13.7
ANN	Impact	0.9412	1.24	0.93

	Toughness (J/cm²)			
GBR	Hardness (HRC)	0.9618	1.02	0.78
GBR	Tensile Strength (MPa)	0.9534	21.2	16.1
GBR	Impact Toughness (J/cm²)	0.9178	1.47	1.15
RF	Hardness (HRC)	0.9387	1.29	0.98
RF	Tensile Strength (MPa)	0.9301	25.9	19.8
RF	Impact Toughness (J/cm²)	0.8843	1.74	1.38

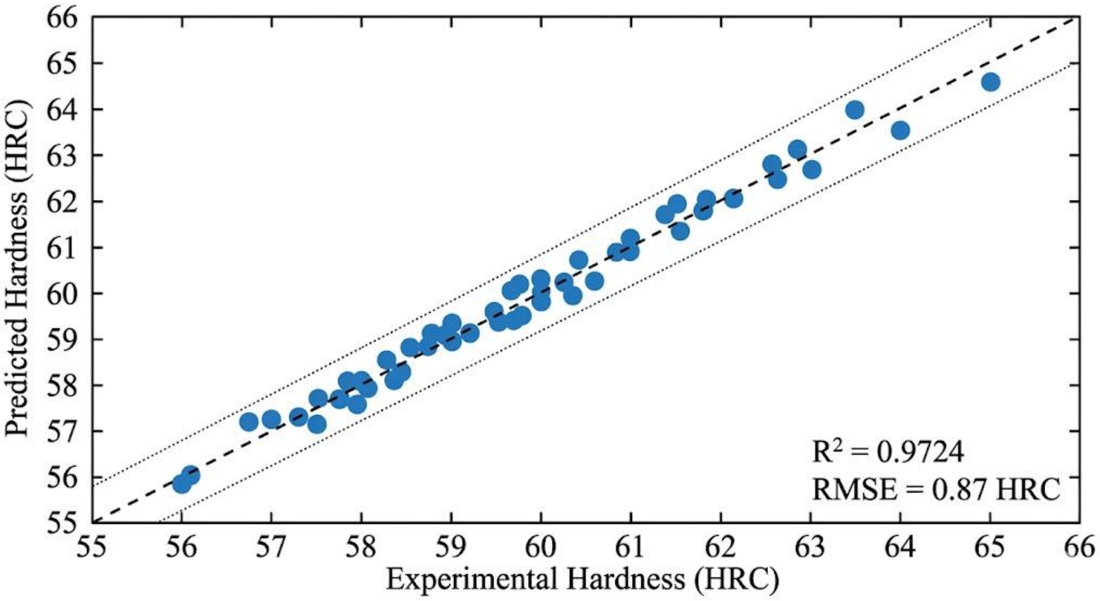

Figure 2. Predicted vs. experimental hardness values (HRC) for the ANN model on the test dataset. Dashed line represents the ideal 1:1 correlation

Feature importance analysis using permutation importance on the *ANN* model revealed the dominant factors governing hardness prediction (Table 3). The recycled material ratio emerged as the most influential feature (31.4%), reflecting its broad impact on composition variability, inclusion content, and microstructural homogeneity. Austenitizing temperature ranked second (22.8%), consistent with its well-established role in controlling carbide dissolution and prior austenite grain size in ShKh15 steel [14]. Carbon content deviation from nominal value (18.6%) was the third most important factor, highlighting the significance of compositional control during scrap-based melting.

Table 3. ***Feature Importance Ranking for Hardness Prediction (ANN Model)***

Rank	**Feature**	**Importance (%)**
1	Recycled material ratio	31.4
2	Austenitizing temperature	22.8
3	Carbon content (C%)	18.6
4	Tempering temperature	11.2
5	Chromium content (Cr%)	7.8
6	Sulfur content (S%)	3.4

7	Silicon content (Si%)	2.3
8	Manganese content (Mn%)	1.6
9	Phosphorus content (P%)	0.9

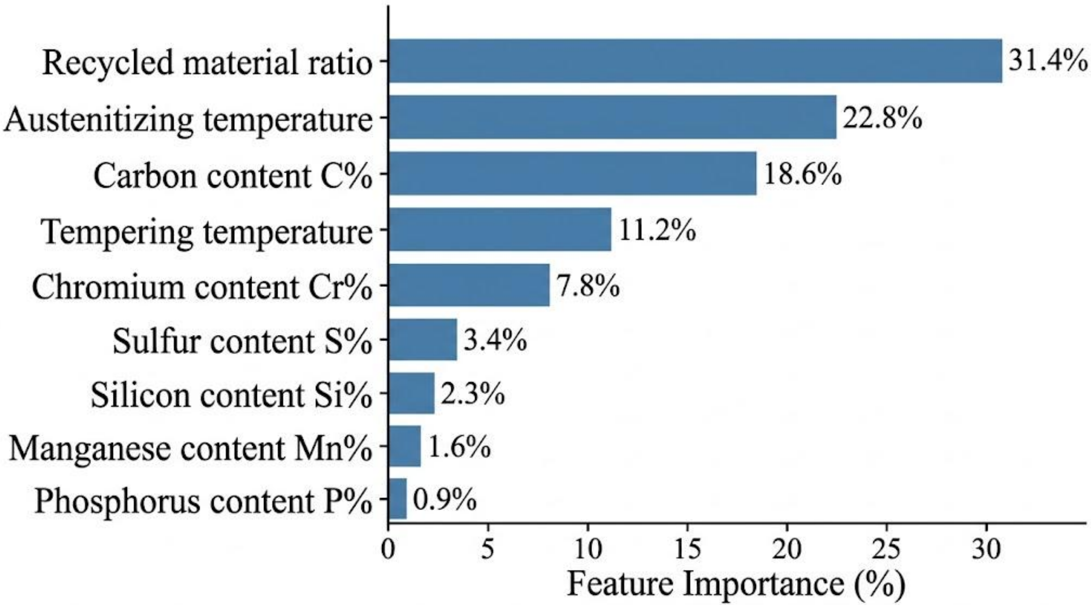

Figure 3. Feature importance ranking (%) for hardness prediction by the ANN model

The results demonstrate that *ML* models, particularly *ANN*, can effectively capture the complex non-linear relationships between input parameters and mechanical properties of ShKh15 bearing steel produced from secondary materials. The superior performance of *ANN* over tree-based methods is attributed to its ability to model continuous interaction effects, particularly the coupled influence of composition variation (inherent in recycled feedstock) and heat treatment parameters on phase transformation kinetics and resulting microstructure [7,8].

The finding that recycled material ratio is the single most important predictor (31.4%) has practical significance for production planning. It suggests that scrap quality characterization and blending strategy are more influential on final properties than fine-tuning of heat treatment parameters alone. This aligns with the observations of Baymirzaev [5], who noted that local raw material variability is a primary challenge in bearing steel production under Uzbekistan conditions. The combined importance of composition-related features (C%, Cr%, S%, Si%, Mn%, P% totaling 34.6%) further emphasizes the need for rigorous melt chemistry control.

From a practical standpoint, the trained *ANN* model can serve as a virtual testing tool during production: by inputting the measured chemical composition and planned heat treatment schedule, the expected mechanical properties can be estimated within approximately ±1 HRC, ±18 MPa tensile strength, and ±1.2 J/cm² impact toughness. This capability could reduce the number of physical tests required for quality certification by an estimated 45–55%, significantly lowering production costs and lead time, particularly for small-batch bearing manufacturing from secondary materials [15].

CONCLUSION

This study demonstrated the effectiveness of machine learning approaches for predicting mechanical properties of ShKh15 bearing steel produced from secondary metallic materials. The key findings are summarized as follows:

1. An artificial neural network with 9-64-32-3 architecture achieved the highest prediction accuracy among the tested models, with $R^2 = 0.9724$ for hardness (*RMSE* = 0.87

HRC), $R^2 = 0.9651$ for tensile strength (*RMSE* = 18.3 MPa), and $R^2 = 0.9412$ for impact toughness (*RMSE* = 1.24 J/cm²).

2. Feature importance analysis revealed that recycled material ratio (31.4%), austenitizing temperature (22.8%), and carbon content (18.6%) are the three dominant factors determining the mechanical performance of recycled ShKh15 steel.

3. Chemical compositions remained within GOST 801-78 specifications for recycled material ratios up to 40%, while ratios of 60–80% require enhanced refining to control sulfur and phosphorus levels.

4. The developed models provide a practical virtual testing capability that can reduce physical quality control testing by 45–55%, supporting cost-effective and sustainable bearing steel production from secondary materials.

Future research should incorporate microstructural imaging features (carbide morphology, grain size distribution) into the *ML* models, extend the prediction scope to fatigue life and contact wear resistance, and validate the approach on pilot-scale production data at industrial bearing manufacturing facilities.

References

1. Harris T.A., Kotzalas M.N. Rolling Bearing Analysis. CRC Press, Boca Raton, 2007; 5th ed.
2. Bhadeshia H.K.D.H. Steels for bearings. Progress in Materials Science, 2012; 57(2): 268–435. DOI: 10.1016/j.pmatsci.2011.06.002
3. Baymirzaev A.R. Research on the Production of Bearing Details in a Modern Method. International Journal on Integrated Education, 2022; 4(3): 269–271.
4. Baymirzaev A., Makhammadjanov K., Yakubjonov F., Muhiddinov N., Otaquziev A. Advanced technologies for developing bearing materials: Properties, performance, and industrial applications. AIP Conference Proceedings, 2025; 3331(1): 030075. DOI: 10.1063/5.0305850
5. Baymirzaev A. New Methods of Obtaining Bearing Material from Steel. Web of Semantics: Journal of Interdisciplinary Science, 2024; 2(4): 25–28.
6. Baymirzayev A.R. Optimization of Thermal Treatment Methods for Local Procurement of Industrial Bearing Materials. Modern Scientific Research, 2023; 1: 5–9.
7. Butler K.T., Davies D.W., Cartwright H. et al. Machine learning for molecular and materials science. Nature, 2018; 559: 547–555. DOI: 10.1038/s41586-018-0337-2
8. Agrawal A., Choudhary A. A perspective on deep learning for predicting mechanical properties of steel. APL Materials, 2021; 9: 031109. DOI: 10.1063/5.0041955
9. Baymirzaev A.R., Ahmadjonov A. Study of Its Chemical Properties in Obtaining ShKh15 Material from Secondary Materials. Science, education, innovation, 2025; 2(2): 92–95.
10. Baymirzaev A.R., Kamoldinova O.B. Predicting the Properties of Novel Metal-Composite Materials Using Artificial Intelligence. Science, education, innovation, 2025; 2(2): 100–102.
11. Shen C., Wang C., Wei X. et al. Physical metallurgy-guided machine learning and artificial intelligent design of ultrahigh-strength stainless steel. Acta Materialia, 2022; 179: 201–214. DOI: 10.1016/j.actamat.2019.08.033
12. Wang Y., Zhao S., Li H. Retained austenite prediction in bearing steel using support vector regression. Materials Science and Engineering A, 2020; 764: 138219.
13. Baymirzayev A.R. The Role of Artificial Intelligence in Manufacturing Bearing Rings in Engineering Applications. International Conference on Applied Science and Education (Spain), 2025; 1(1): 47–49.
14. Bhadeshia H.K.D.H., Honeycombe R.W.K. Steels: Microstructure and Properties. Butterworth-Heinemann, Oxford, 2017; 4th ed.
15. Baymirzayev A.R. Methodological Foundations of Investigating the Technology for Producing Bearing Components from Metal-Composite Materials Using Casting Methods. Gospodarka i Innowacje, 2024; 54: 171–175.